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Spatial Analysis of Forest Crimes in Mark Twain National Forest, Missouri

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Abstract

Forest crime mitigation has been identified as a challenging issue in forest management in the United States. Knowledge of the spatial pattern of forest crimes would help in wisely allocating limited enforcement resources to curb forest crimes. This study explores the spatial pattern of three different types of forest crimes: fire crime, illegal timber logging crime, and occupancy use crime in the Salem-Patosi Ranger District of Mark Twain National Forest. Univariate and bivariate Ripley's K-functions were applied to explore the spatial patterns in crime events, like clustering and attraction among forest crime types. Results reveal significant clustering for each forest crime type and the combined events. Peak clustering was observed at 2.3 km, 2.7 km and 3.6 km for fire, timber and occupancy use crimes, respectively. For better forest crime mitigation, when there is an event of a given forest crime type, monitoring should be intensified around its respective spatial scale of peak clustering to avert future crime events. Significant attraction was observed between i) fire crime and illegal timber logging crime, and ii) fire crime and occupancy use crime, at spatial scales of 0.3 km and 0.2 km, respectively. At the respective spatial scales, occurrence of one type of crime increases the chances of occurrence of another type of crime, thus we recommend allocating available resources accordingly to minimize crime events. Further study could help establish any association of clustering or attraction of forest crimes with different socio-economic and bio-physical factors prevalent in and around the area.

Keywords: clustering, fire crime, forest crime, Ripley's K-function, spatial pattern

Introduction

Forest crimes involve unlawful activities that take place inside or surrounding forest areas. Illegal timber logging, illegal occupation of forestland, and woodland arson have been identified, among others, as some of the most notorious forest crimes prevalent in both developing and developed countries. Forest crimes can severely affect the environmental, ecological, and social services provided by forests, and thus are serious threats to sustainable forest

management (Contreras-Hermosilla 2002, Kishor and Belle 2004, World Bank 2006). To manage forest resources in an efficient manner, it is important to understand the trends and patterns of forest crimes.

Among the different types of serious forest crimes, fire crime has the greatest potential to significantly alter the condition of the forest, as it influences vegetation composition and structure, reshapes the landscape mosaic, and affects biogeochemical cycles (Flannigan et al. 2000). Knowledge of spatial patterns of fire occurrence and their relationships to underlying factors of human risk can locate and make prevention efforts more efficient (Martinez et al. 2009). In a similar way, illegal timber logging not only impacts the forest ecosystem and biodiversity, but also affects the marketplace where legitimate forest enterprises would face unfair competition through price undercutting. One study from the U.S. found that domestic roundwood prices would be 2-4 percent higher and U.S. exports of wood products about \$460 million more per year, if competition from illegal producers was eliminated (World Bank 2006).

Spatial pattern analysis of forest crime occurrences has been recognized as an important component for mitigation efforts (Wing and Tynon 2008, Tynon and Chavez 2006). Results from such studies can be used to identify hot spots and predict likely locations of future occurrences. This could lead to an increased efficiency in the allocation of resources to reduce forest crimes. Findings from earlier studies have shown that forest crimes, in general, exhibit a clustering pattern. One such study by Wing and Tynon (2006) on crime mapping and spatial analysis in USDA Forest Service lands identified that crime hot spots tend to concentrate in those forests which are adjacent to population centers and transportation. In a different study, Wing and Tynon (2008) found increased number of crime incidents in corridors near recreation destination sites, campsites and water features. Narayanaraj and Wimberly (2012) studied the Okanogan-Wenatchee National Forest and its neighboring forested lands in Washington State and found that road corridors significantly influenced the spatial pattern of human-caused fire ignitions. The locations of human-caused ignitions were concentrated in close proximity to gravel roads and were located where there were high densities of both gravel and paved roads. Likewise, a study from Florida showed positive correlation between human induced fire and difficult economic conditions (Prestemon and Butry 2005). However, very few studies have used K-function to analyze the spatial pattern of forest crimes in particular. Wing and Tynon used nearest neighborhood, kernel density methods, and quadrat analysis to carry out spatial analysis of forest crimes in National Forests (Wing and Tynon 2006, Wing and Tynon 2008). Yang et al. (2007) used kernel density and K-function to assess the spatial pattern of human-caused fire in Missouri Ozark Highlands. They also used lurking variable plot as a tool for residual analysis to examine the quality of a fitted-model for fire occurrence. Results from that study also suggested clustering patterns of human-caused fire in the forest. Distance to roads and distance to the nearest town were found to influence the density of fire occurrence.

Objectives

The objective of this paper is to examine spatial relationships at and between different forest crimes to enhance monitoring and mitigation strategies. We investigate the spatial patterns of three different types of forest crimes: forest fire, illegal timber logging (also referred to as ‘timber crime’), and unauthorized occupancy use of forest lands. We first examine the spatial distribution of each pattern separately to identify potential clustering behavior. We then explore spatial dependences between different crime types, in other words whether there is spatial attraction or repulsion and at which spatial scales.

Methods

Study area

This study was based on the data collected from Salem and Potosi areas of Mark Twain National Forest. This national forest covers approximately 6,100 km² and is located in parts of 29 southern and central Missouri counties. The major land cover type in the study area is deciduous forest composed primarily of oak trees, such as red (*Quercus rubra*), white (*Q. alba*), black (*Q. velutina*), scarlet (*Q. coccinea*) and post oak (*Q. stellata*) species (Wang et al. 2007). Rivers and trails in the forest are the main sources of attraction. Ten-year average of wildfire affected area in the forest is 20 - 24 km² per year. Most of the wildfires on Mark Twain National Forest are human-caused where out of the 1,299 fire events recorded from 1970 to 2002, about 74 percent were the result of arson (Yang et al. 2007). Salem and Potosi areas of the Mark Twain National Forest were selected for the study because of their combined shape and size. Salem and Potosi together make the biggest forest patch in the National Forest (approximately 1,500 km²) with a near rectangular shape suited for spatial analysis. The study area is almost entirely covered by forest area and no distinct elevation pattern was observed (USDA 2010). Hence the assumption of absence of major first order spatial pattern seems valid. A rectangular area (approximately 1,150 km²) inside the Salem-Potosi forest patch was used to do the spatial analyses (Figure 1).

Data

Data for this study constituted of observations of three different types of forest crimes; fire crime, timber crime and occupancy use crime (Figure 1). The data was recorded from 2001 to 2010 by Forest Service Law Enforcement Officers (LEO) at the Mark Twain National Forest, and recorded in the Forest Service Law Enforcement and Investigations Management Attainment Reporting System (LEIMARS) database, along with other types of forest crimes. Latitude and longitude information of each forest crime event were also recorded. Fire crime is defined as setting fire to timber, bush, or grass willfully and without authority. Timber crime is defined as illegal cutting, damaging, removing, marking, loading, or hauling of timber and other forest products. Occupancy use crime is defined as illegal construction of roads, trails, structures, unauthorized camping, selling, and any other use. A total of 169 forest crime events were used in the study, which included 70 fire crimes, 38 timber crimes and 61 occupancy use crimes.

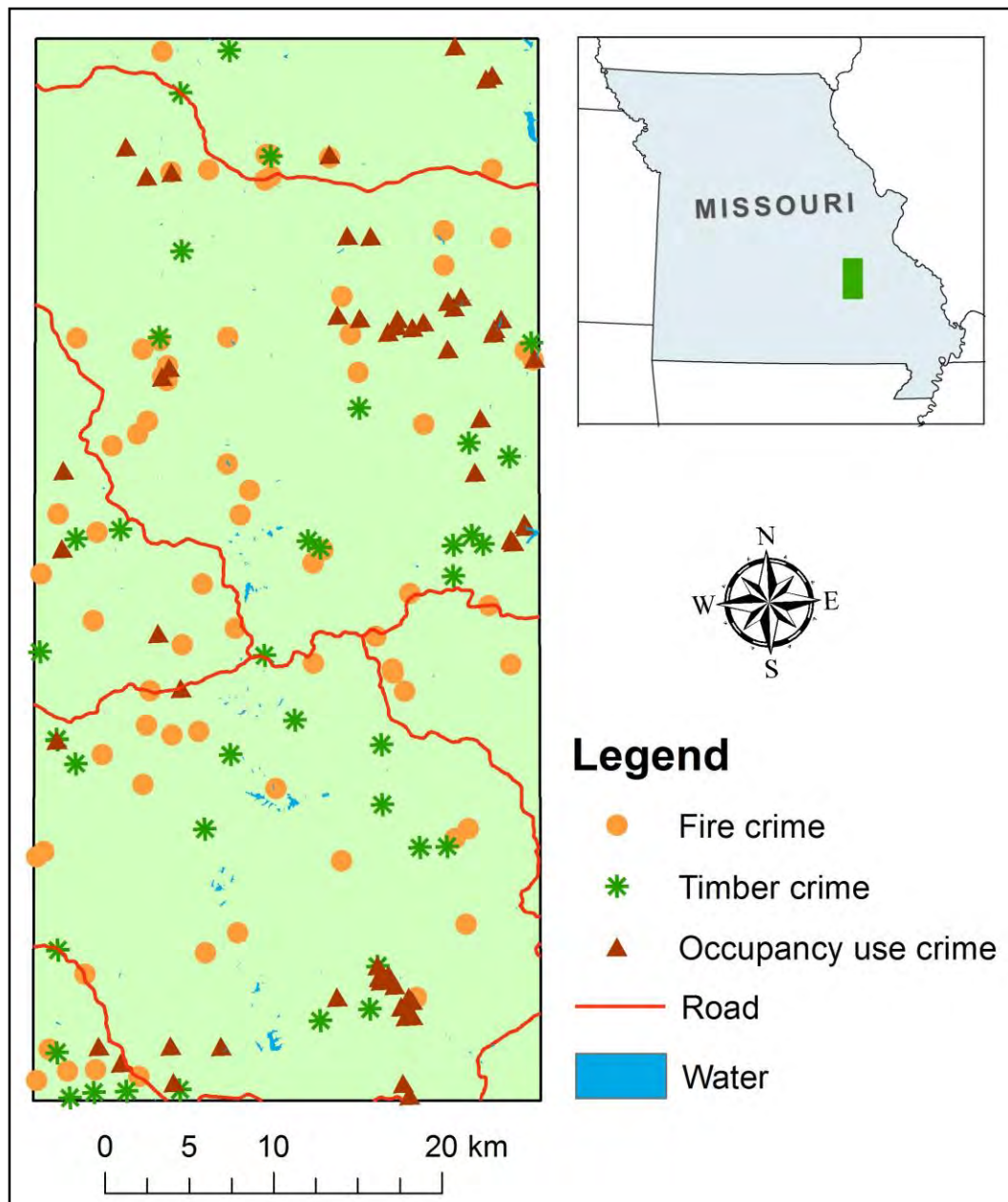


Figure 1. Study area showing location of three different types of forest crimes. Inset map shows the location of study area within the State of Missouri.

Analysis

Different methods have been identified and applied to analyze the spatial pattern of point events. Quadrat analysis and kernel density analysis are typical spatial tools used to explore the first order effects in the study area. First order effects express the spatial variation in the mean value of the events across the space in order to evaluate underlying spatial pattern of the events. Second order effects describe the spatial dependence or interaction between events or the tendency of deviating the values of events from their mean to follow each other in neighboring sites (Bailey and

Gatrell 1995). Although, several statistics have been developed for second order processes, Ripley's K-function is frequently used because it uses information of distance between all possible pair points and provides within-pattern point interactions at multiple scales (Ripley 1977, Moeur 1993, Chen and Bradshaw 1999). K-function makes the assumption of stationarity and isotropic point process, so it is frequently used as a valid second order statistic to test for the null hypothesis of complete spatial randomness (Liu et al. 2007). In this study, we assume that there is no first order effect or any specific directional influence that would violate the isotropic condition. Several studies have been conducted in different fields of forestry using the Ripley's K-function as the underlying spatial methodology. Examples include forest stand characterization (Salas et al. 2006), tree mortality pattern analysis (Liu et al. 2007), regeneration pattern study (Fajardo et al. 2006) and spatial dynamics of species (Lin and Augspurger 2008). Spatial analysis in this study was conducted with custom code in MATLAB. ArcGIS was used to run proximity analyses and to produce the maps in this manuscript.

Univariate K-function

Univariate K-function was used to identify potential spatial distribution for four different cases; i) all three forest crimes together, ii) fire crime, iii) timber crime, and iv) occupancy use crime. The univariate K-function measures spatial randomness of a given set of points. Inference from the univariate K-function analysis could suggest whether the spatial pattern of points can be assessed as random, clustered or regular. In a clustered pattern, points are clumped into one or more groups thus leaving some relatively empty areas in the space. In contrast, a regular pattern has points that are evenly distributed (or dispersed) across the space.

The univariate K-function was calculated using the equation given by Baily and Gatrell (1995),

$$K(h) = \frac{R}{n^2} \sum_{i \neq j} I_h(d_{ij})$$

where, $K(h)$ is the K-function, h is radius of the search circle, R is the total study area, n is the number of events, d_{ij} is the distance between i^{th} and j^{th} event, I_h is an indicator function which is 1 if $d_{ij} \leq h$ and 0 otherwise. The K-function calculates the average number of additional events within a search distance of h from a randomly chosen event normalized by the overall density of events in the study area.

The Complete Spatial Randomness (CSR) test was used to test whether the observed point patterns are random, regular or clustered. CSR for spatial point pattern assumes that every location in the study area has an equal chance of receiving a point, and points have no effect on each other. Under constant intensity Poisson process Ripley's K-function, $K(h) = \pi h^2$. If there is clustering, $K(h)$ is larger than it would be under CSR and it is smaller for regularity (Bailey and Gatrell 1995, Diggle 1983, Mateu et al. 1998, Cressie 1993, Serra et al. 2013). The L-function, which is a square root transformation of K-function, linearizes K and stabilizes its variance, and is approximately zero under the assumption of Poisson process (Boyden et al. 2005, Moeur 1993). The L-function, given below, would compare whether the observed spatial pattern is different from CSR or not.

$$L(h) = \sqrt{\frac{K(h)}{\pi}} - h$$

where $L(h)$ is the L-function, π is a constant and others as described above.

For every experiment, we conducted ten thousand random simulations and reported the 95% confidence interval for the L-function to plot upper and lower confidence envelopes for the test.

Bivariate K-function

The bivariate or Cross K-function was used to explore spatial association between two sets of events; i) fire crime and timber crime, and ii) fire crime and occupancy use crime, against the hypothesis of spatial independence. Spatial association can be considered as independent, attraction or repulsion. Independence in the spatial patterns of two sets of events is when no association exists in the location of events. Attraction is when one set of points are closer to the other set of points relative to the independent distribution, while repulsion is when distance between two sets of points are farther than expected under independence. The bivariate K-function is given by the equation (Bailey and Gatrell 1995),

$$K_{ij}(h) = \frac{R}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} I_h(d_{ij})$$

where, $K_{ij}(h)$ is the K-function from one set of points to another set of points, R is the study area, n_1 is the number of one set of events, n_2 is the number of another set of events, I_h is an indicator function which is 1 if $d_{ij} \leq h$ and 0 otherwise. This equation calculates the average number of type one events within a search distance of h from type two events normalized by the density of type one events in the study area (Boyden et al. 2005, Bailey and Gatrell 1995). Under the assumption of a stationary process, the cross K-function from type one of events to type two events $K_{12}(h)$ is equal to that from type two events to type one events $K_{21}(h)$. Edge correction was not taken into consideration while doing this analysis because there would be bias in K-function for higher spatial scale (h) values (Dixon 2002).

To calculate the range of spatial independence in the bivariate K-function, a toroidal shift was applied. Locations of the whole type one events were shifted by a random distance and a random direction while keeping the locations of type two events constant (Bailey and Gatrell 1995). This method is useful in testing the hypothesis of independence between two types of populations whose specific spatial pattern can, a priori, be the result of different processes (Goreaud and Pelissier 2003). Since one type of event would be shifted across the study area, we assume there are no constraints in the study area and events are possible to happen across the study area (Bailey and Gatrell 1995, Dixon 2002).

Results

Spatial distribution of clustering/regularity of each forest crime

Events of all three forest crimes (fire crime, timber crime and occupancy use crime) combined together exhibited a strong and significant clustering pattern (Figure 2a) ranging from spatial scale of 0.1 to 7.6 km. The peak of this clustering pattern was seen at the spatial scale of 2.9 km (Figure 2b). A random pattern was visible beyond the spatial scale of 7.6 km. The radius of the search circle shown below (Figure 2c) corresponds to the lag distance (2.9 km) where maximum clustering was observed for the forest crime events. Results from this study, revealing clustering pattern for forest crimes, is similar to earlier studies that identified forest crime hot spots near population

centers, transportation routes, recreation centers, campsites and water resources (Wing and Tynon 2006, Wing and Tynon 2008). Forest crimes in our case seem to be clumped close to road network and water bodies. Frequencies of crime events for incremental distances from road and water bodies were calculated. Results showed that the forest crimes were clumped closer to road network, as higher numbers of crimes were observed nearer to roads compared to distant areas (Figure 3a & 3b). When crime frequencies were observed with distance from water, a different pattern was observed, with highest number of crime events falling in between 4 to 6 km of water bodies (Figure 3c & 3d). Law enforcement resources and efforts can be concentrated in these hot spot areas to efficiently minimize the crimes.

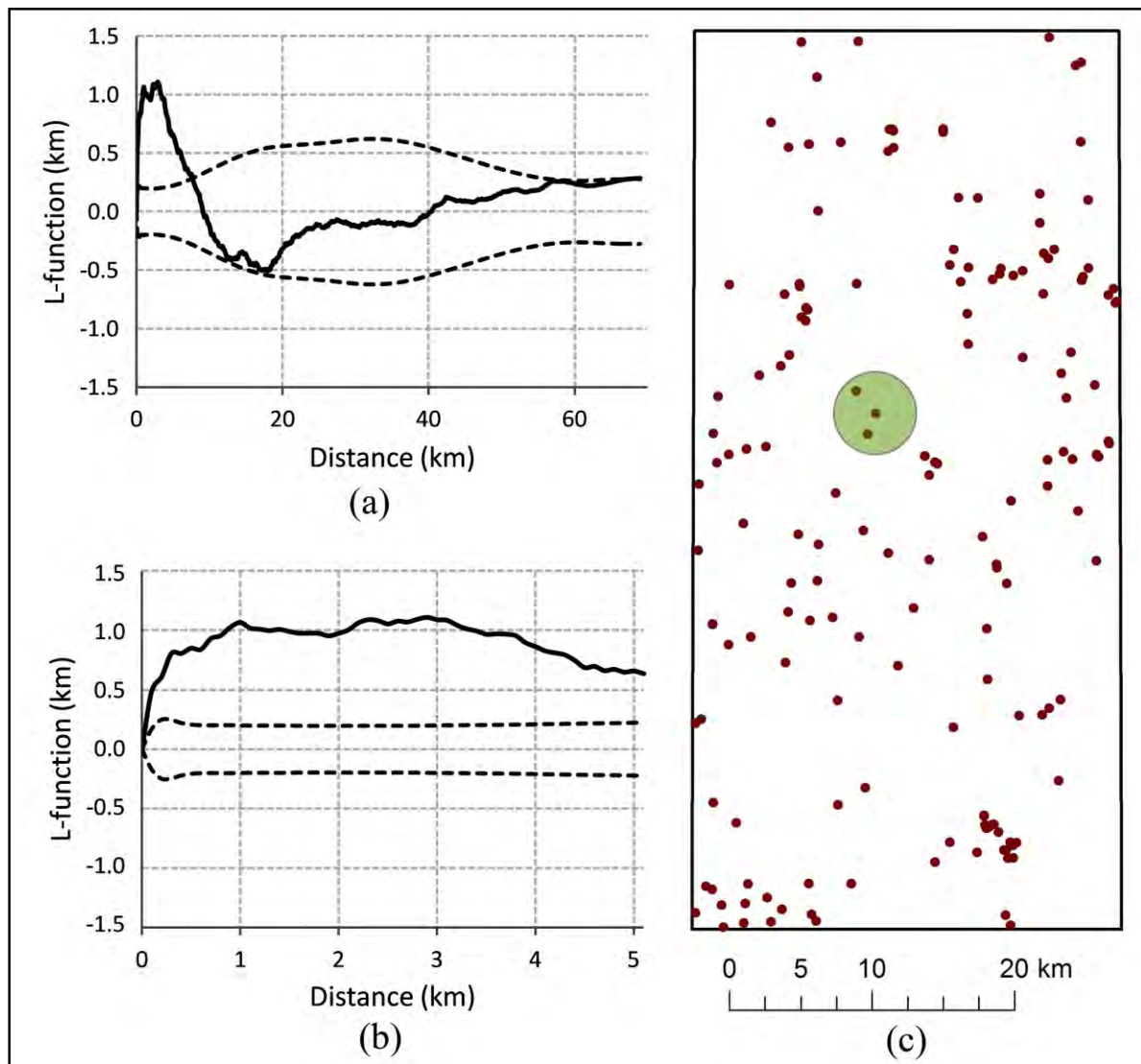


Figure 2. L-function (km) for all three crimes (solid line) plotted against distance (km), dashed lines are 95% upper and lower confidence envelope (a), L-function zoomed in to show nearest 5 km (b), forest crime events shown in brown dots and a circle representing search distance of 2.9 km for maximum clustering (c).

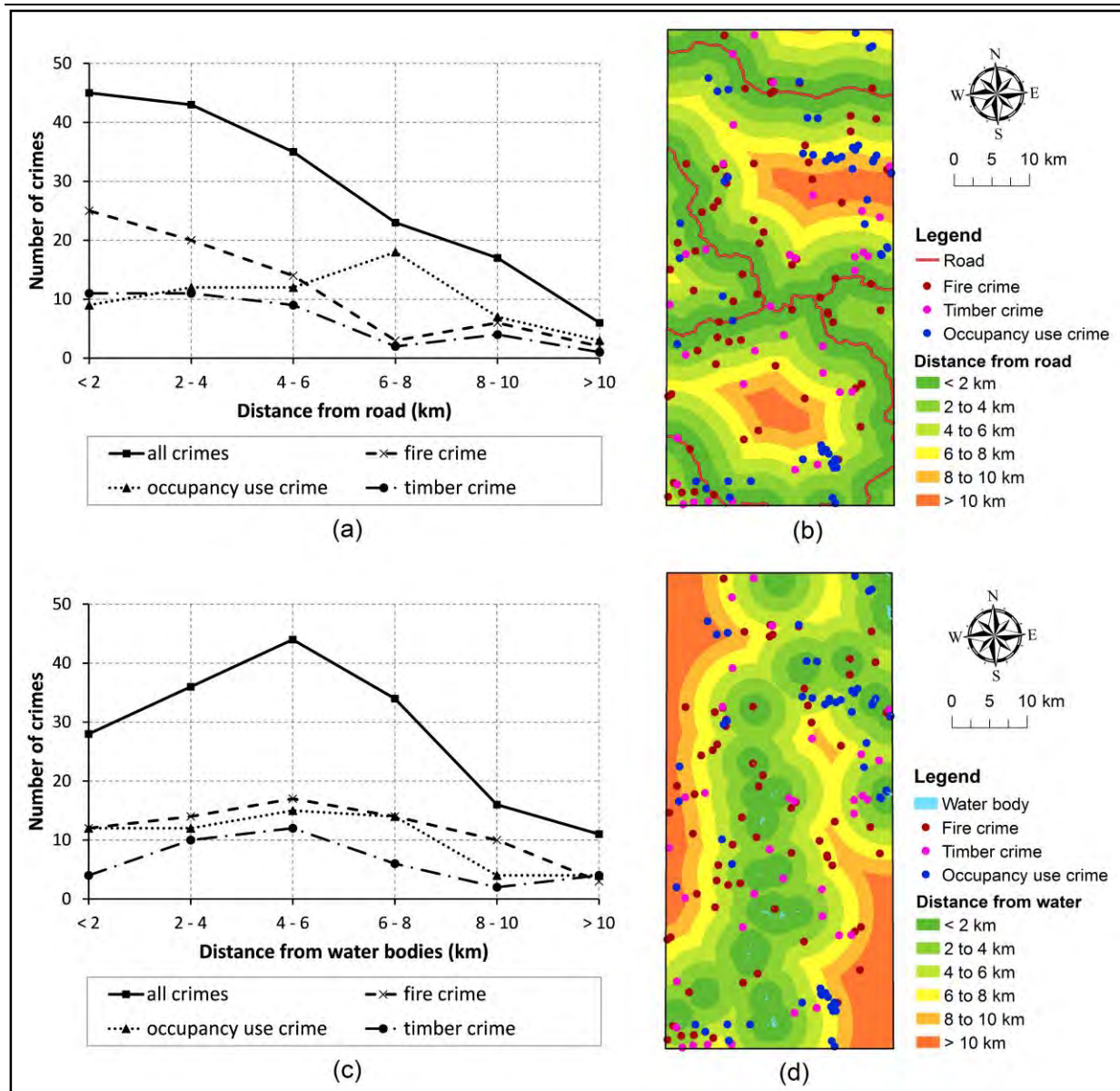


Figure 3. Number of forest crimes for incremental distances from road (a), distance from road and locations of crimes (b), number of crimes corresponding to incremental distances from water bodies (c), distance from water bodies and location of crimes (d).

In the case of fire crime, there was a clustering pattern at distances ranging from 0.3 to 4.3 km (Figure 4a & 4b) with peak of clustering observed at the distance of 2.3 km. Another clustering was also seen for lag distances greater than 30 km (Figure 4a), however, this result may not have much significance because of the influence of edge effects at this scale. This finding is similar to other studies (Narayanaraj and Wimberly 2012, Amatulli et al. 2007), suggesting an association of one fire crime to another fire crime in small spatial scales. In cases when a fire crime event is observed, prevention measures should be intensified at least within the spatial scales of about 4.3 km, where there is

high possibility of another fire crime event occurring. Fire crime was found to be clumped closer to the roads (Figure 3a & 3b), which would require a strong law enforcement presence along road and trail areas for the minimization of this crime.

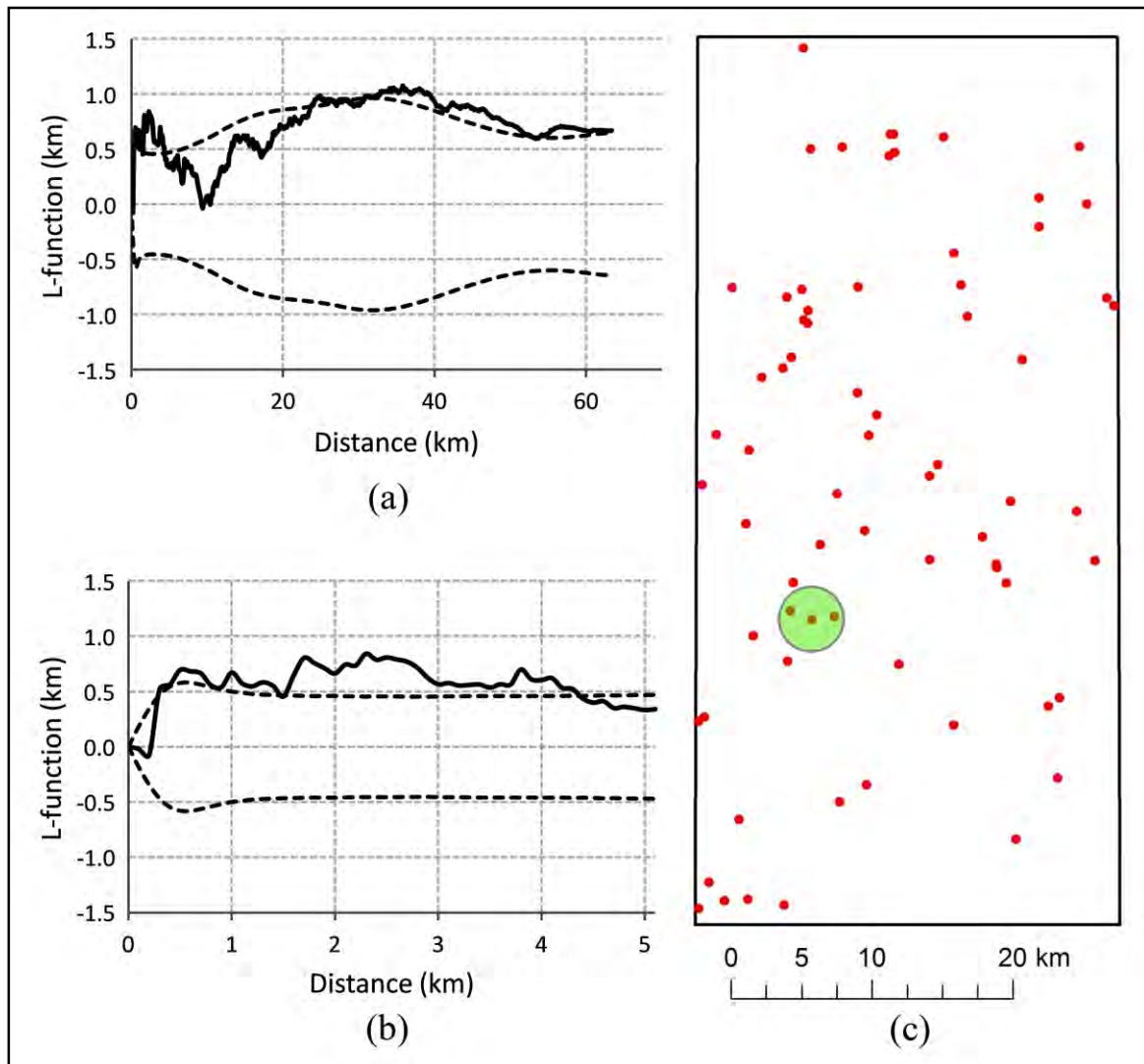


Figure 4. L-function for all fire crime (solid line) plotted against distance (km), dashed lines are 95% upper and lower confidence envelope (a), L-function zoomed in to show nearest 5 km (b), fire crime events shown in red dots and a circle representing search distance of 2.3 km for maximum clustering (c).

A clear clustering pattern for the timber crime was observed at two different spatial scales (Figure 5a & 5b). First clustering was seen at smaller scale from around 0.1 to 0.4 km and another clustering was identified from 1.9 to 3.7 km. The peak of clustering was located at approximately 2.7 km lag distance. Timber crimes were relatively higher in number in areas close to roads, though this trend was not as strong as it was for fire crime (Figure 3a & 3b). On

the other hand, higher concentration of timber crime was seen at a distance of 2 to 6 km from water bodies (Figure 3c & 3d).

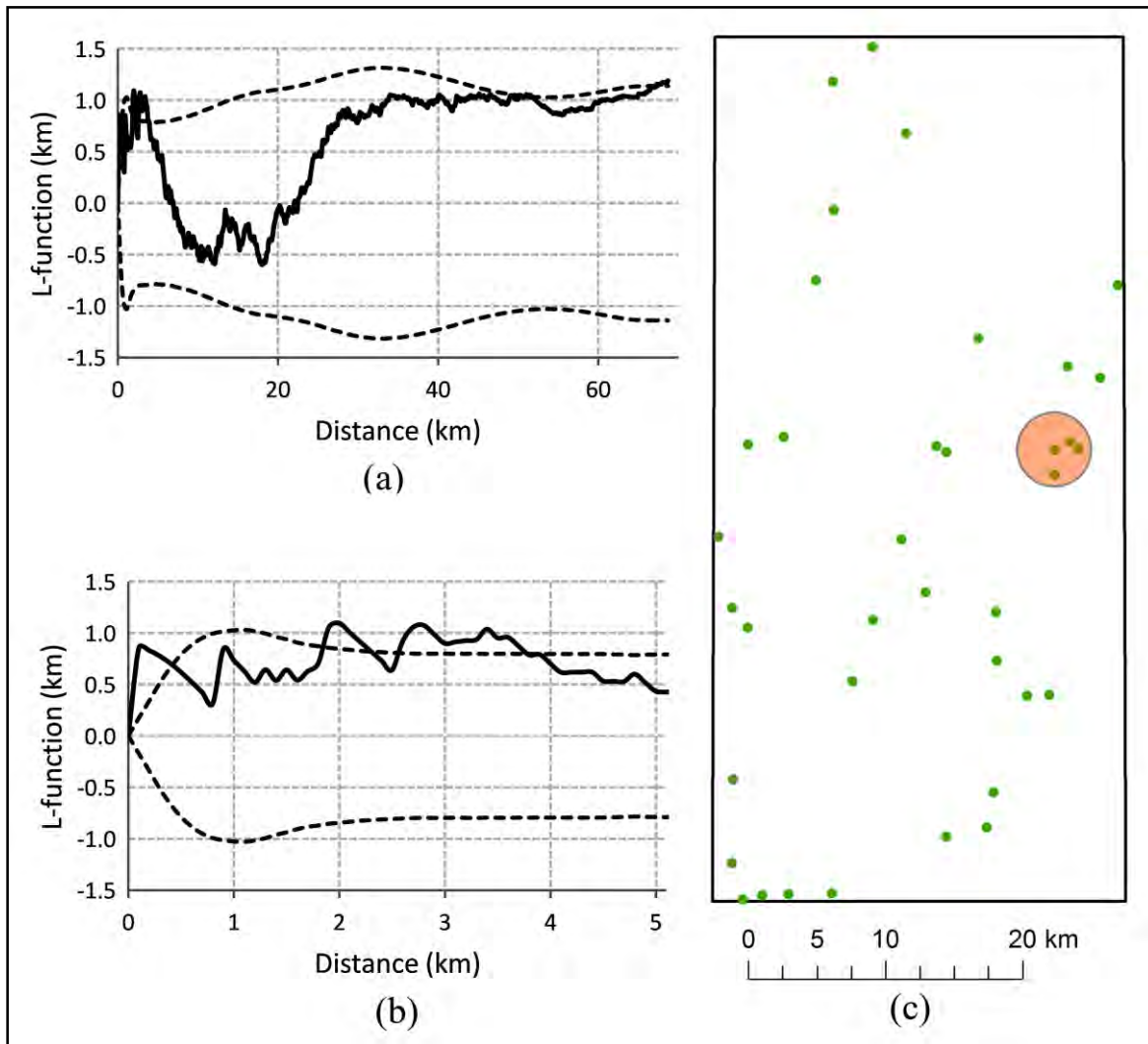


Figure 5. L-function for timber crime (solid line) plotted against distance (km), dashed lines are 95% upper and lower confidence envelope (a), L-function zoomed in to show nearest 5 km (b), timber crime events shown in green dots and a circle representing search distance of 2.7 km for maximum clustering (c).

A distinct clustering pattern was observed for the occupancy use crime events. Significant amount of clustering was seen from 0.1 to 16.2 km (Figure 6a) with strongest clustering at the spatial scale of 3.6 km (Figure 6b & 6c). In addition, a regular pattern was also visible for these crime events from 24 to 42 km lag distances. Results at such a large spatial scale relative to the size of study area hold little meaning due to the role of edge effects. Strong influence of clustering pattern of occupancy use crime over the clustering pattern of overall forest crimes was revealed. This was apparent since the spatial scale of maximum clustering and the pattern of L graphs was similar

for both occupancy use and overall forest crimes. Unlike fire crime which was more abundant closer to roads, occupancy use crime was found in higher numbers at a distance of 6 to 8 km from roads (Figure 3a & 3b). Occupancy use crime was found in higher frequency at a distance of 4 to 8 km from water bodies even though this trend was not as strong (Figure 3c & 3d).

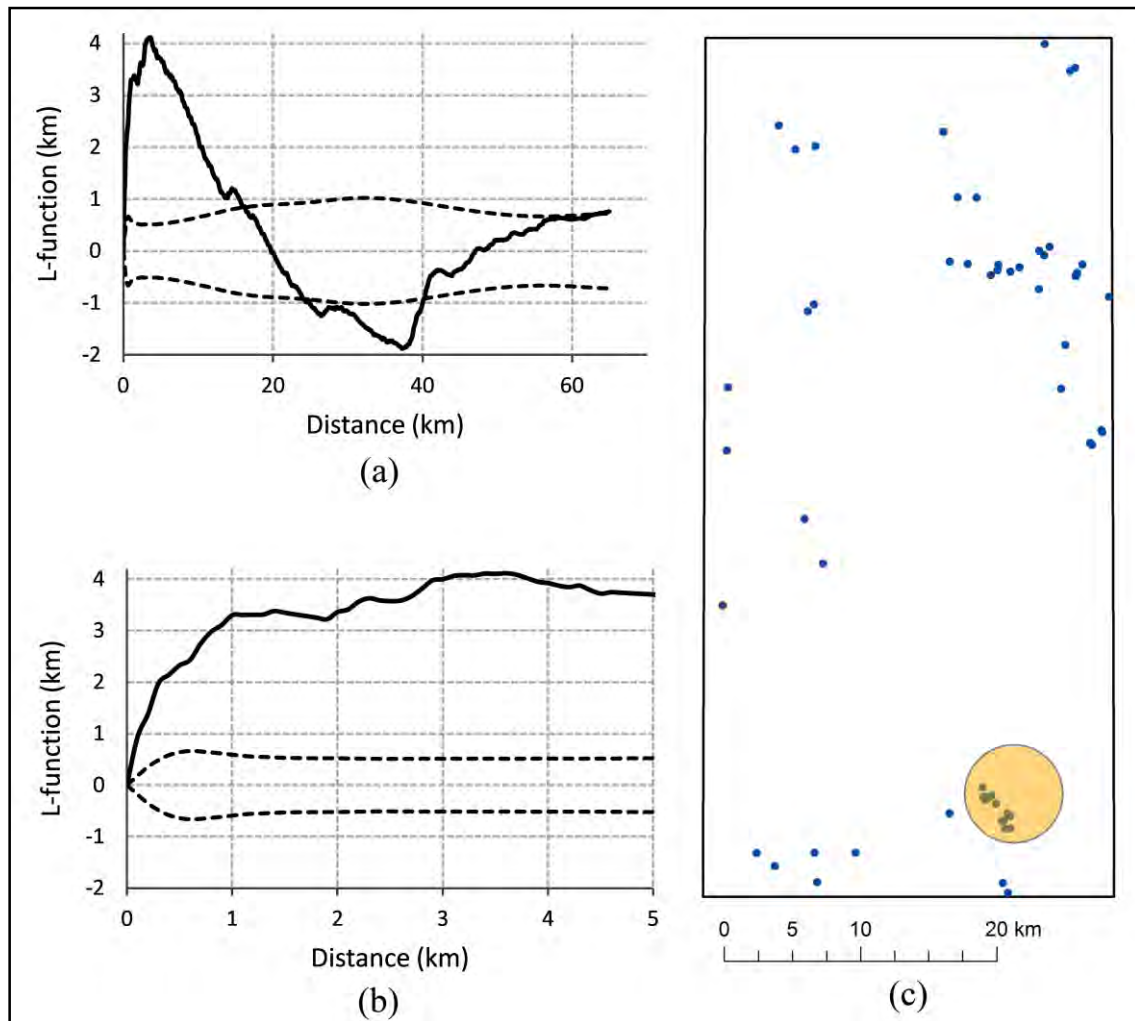


Figure 6. L-function for occupancy use crime (solid line) plotted against distance (km), dashed lines are 95% upper and lower confidence envelope (a), L-function zoomed in to show nearest 5 km (b), occupancy use crime events shown in blue dots and a circle representing search distance of 3.6 km for maximum clustering (c).

Pairwise comparison of attraction/repulsion between forest crimes

Strong spatial dependence in the form of attraction was seen between fire crime and timber crime at short lag distances ranging from around 0.2 to 0.5 km (Figure 7a & 7b), peaking at around 0.3 km. The result supports our hypothesis that there is some association between fire and timber crimes. However, a further investigation is warranted to infer whether timber crime leads to fire crime, or vice-versa. Nevertheless, law enforcement personnels

might take necessary precautionary steps to reduce either fire or timber crime by looking at the incidence of the other type of crime within the given spatial scale.

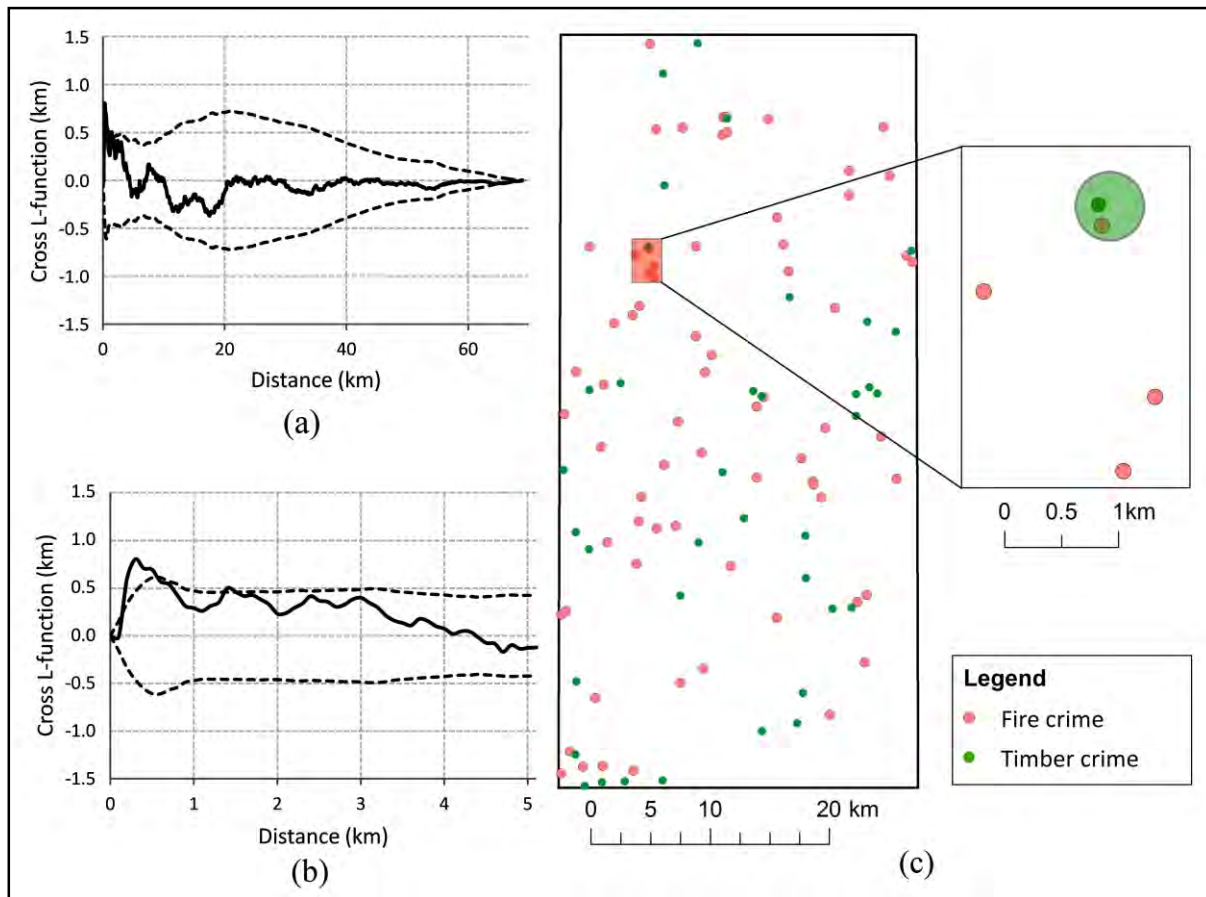


Figure 7. Cross L-function between fire crime and timber crime (solid line) plotted against distance (km), dashed lines are 95% confidence envelopes (a), Cross L-function zoomed in to show nearest 5 km (b), fire crime events shown in red dots and timber crime events shown in green dots. Rectangular area zoomed in to show the circle that represents a search distance of 0.3 km for their maximum dependence (c).

Similar to the previous pair comparison, spatial dependence (attraction) between fire and occupancy use types is identified at smaller spatial scale from about around 0.1 to 0.4 km (Figure 8a & 8b), peaking at 0.1-0.2 km lag distances. Between fire crime and occupancy use crime, there is attraction at smaller spatial scale, which means that at relatively smaller spatial scales, fire crime could lead to the possibility of occupancy use crime or vice-versa. This result would also be useful for law enforcement efforts because it indicates that after the occurrence of either of these crimes, enforcement resources should be mobilized to control the possibility of other type of crime associated with it.

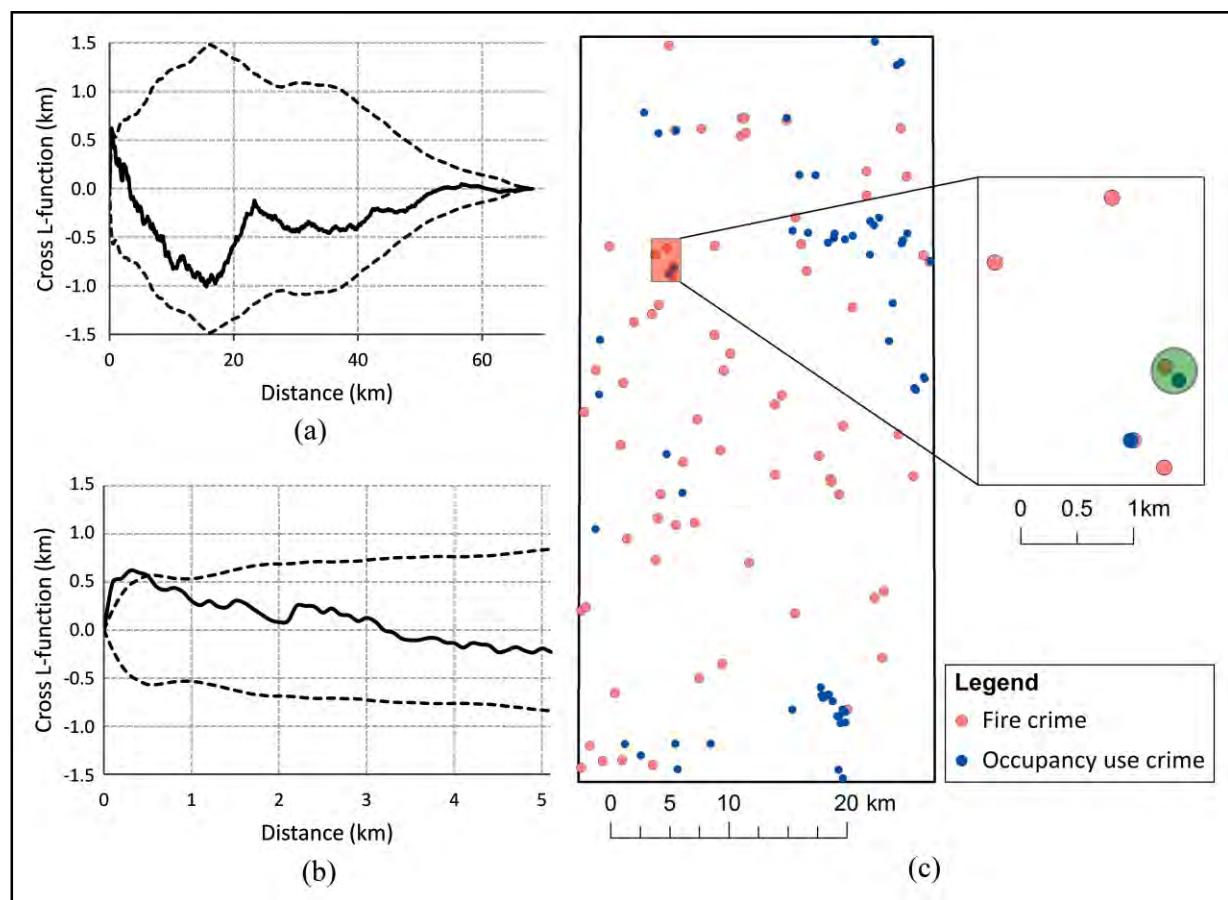


Figure 8. Cross L-function between fire crime and occupancy use crime (solid line) plotted against distance (km), dashed lines are 95% confidence envelopes (a), Cross L-function zoomed in to show nearest 5 km (b), fire crime events shown in red dots and occupancy use crime events shown in blue dots. Rectangular area zoomed in to show the circle that represents a search distance of 0.2 km for their maximum dependence (c).

Conclusions

This study was carried out using univariate and bivariate Ripley's K-function to analyze the spatial pattern of different types of forest crime events. Univariate K-function was applied to investigate the hypothesis of clustering or regularity among different types of forest crimes. Bivariate K-function was used to assess the hypothesis of spatial independence between two different types of forest crimes. Results exhibit significant clustering patterns for individual and collective forest crime events.

Forest management efforts should take note of these hot spots and devise efficient policy and resources to minimize the crimes. Significant attraction was observed between i) fire and timber crime and ii) fire and occupancy use crime, suggesting that the occurrence of one type of these crime leads to another type of crime or vice-versa. This type of information, where we can anticipate the probability of one type of crime event based on the occurrence of another type of crime within given spatial scale, is useful for forest enforcement personnel when monitoring and preventing crimes. Further studies on possible linkages between clusters in forest crimes with additional socio-

economic and bio-physical attributes like urban centers, population and hydrology could be built on these findings. Exploration of temporal pattern, which is outside the scope of this study, could suggest more detail recommendations on the possibility of future crime.

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